Estimation of latency on production grid over several weeks

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ABSTRACT
Previous works have presented a probabilistic model of the latency of the grid depending on parameters characterizing the workload. In this paper, we study both the validity of parameters along several weeks and the influence of the day of the week. We show that performance can be improved by the actualization of model parameters.

Keywords
grid computing, model, context

1. INTRODUCTION
Grids are powerful tools for large scale studies on medical data and specifically on medical images. However, the behavior of grids is highly variable and they are subject to faults. We thus need to model the grid in order to improve job submissions and estimation of performance.

Our approach consists in probabilistic modeling using execution context parameters. Preliminary works [2, 7] have shown the validity of the model. However these studies have been made on a very short period of time thus hiding the temporal variability of workload conditions. In this paper, we enlarge our study along several weeks in order to study the model temporal validity.

2. RELATED WORKS
Several initiatives aim at modeling grid infrastructure Workload Management Systems (WMS). In [5], correlations between job execution properties (job size or number of processors requested, job run time and memory used) are studied on a multi-cluster supercomputer in order to build models of workloads, enabling comparative study on system design and scheduling strategies. In [9], authors make predictions of batch queue waiting time which improves the total execution time.

Taking into account contextual information has been reported to help in estimating single jobs and workflows execution time by rescheduling. Feitelson [1] has observed correlations between run time and job size, number of cluster and time of the day. In [8], the influence of changes in transmission speed, in both executable code and data size, and in failure likelihood are analysed for a better estimation of end time of sub-workflows. This is used for re-scheduling jobs after fault or overrun.

Authors of [10] analyze job inter-arrival times, waiting times at the queues, execution times and data exchange sizes. They conducted experiments on the EGEE grid on several VOs (Virtual Organizations) and studied the influence of the day of the week and the time of the day. Their conclusion on these influences is that there is an increase of the load at the end of the day but that it is difficult to extract a precise model of the behavior with respect of the day or the time.

To refine grid monitoring, [11] presents a model of the influence between the grid components and their execution context (system and network levels), experimented on Grid'5000.

In previous work, we have shown that some of the parameters of the execution context have an influence on the expectation of job execution time [2, 7]. In this work, we focus on the validity of our parameters along several weeks and we refine the study on the day of the week.

3. EXPERIMENTAL PLATFORM
Our experiments are based on biomed VO of the EGEE production grid infrastructure. With 40000 CPUs dispatched world-wide in more than 240 computing centers, EGEE represents an interesting case study as it exhibits highly variable and quickly evolving load patterns that depend on the concurrent activity of thousands of potential users. Even if the infrastructure is relatively homogeneous from the OS point of view (Scientific Linux), important architecture and performance variations are expected among the worker nodes (64/32 bit machines, multi/single processor).

For the following discussion, the main components of the batch-oriented EGEE grid infrastructure are introduced. When a user wants to submit a job from her workstation, she connects to an EGEE client known as a User Interface. A Resource Broker (RB) queues the user requests and dispatches them to the different computing centers available. The gateway to each computing center is one or more Computing Element (CE). A CE hosts a batch manager that will distribute the workload over the center Worker Nodes, using different batch queues. Different queues handle jobs with different wall clock times. However the policies for deciding of the number of queues and the maximal time assigned to each of them are site-specific.

During its life-cycle, a job is characterized by its evolving status. If everything happened as expected, the job is then *completed*. Otherwise, it is *aborted*, *timed-out* or in an *error* status depending on the type of failure.

4. MODEL OF THE LATENCY

Models of the grid latency enable the optimization of job submission parameters such as jobs granularity or the timeout value needed to make the WMS robust against system faults and outliers. Properly modeling a large scale infrastructure is a challenging problem given its heterogeneity and its dynamic behavior. In a previous work, we adopted a probabilistic approach [3] which proved to improve application performances while decreasing the load applied on the grid middleware by optimizing jobs granularities. Similar probabilistic models have been proposed to estimate timeouts in other complex systems [12, 6].

In [4], we have shown how the distribution of the grid latency impacts the choice of a timeout value for the jobs. We model the grid latency as a random variable R with probability density function (pdf) f_R and cumulative density function (cdf) F_R. The optimal timeout value can be obtained by minimizing the expectation of the job execution time J which can be expressed as a function of R, the timeout t_∞ and the proportion of outliers ρ:

$$E_J(t_\infty) = \frac{1}{F_R(t_\infty)} \int_0^{t_\infty} u f_R(u) du + \frac{t_\infty}{(1-\rho)F_R(t_\infty)} - t_\infty \quad (1)$$

Experimental measures show high variability in the latency. In this paper, we present two different studies aiming at reducing this variability and improving job execution on production grids. First, we study the evolution of the optimal timeout and the expectation of the job execution time over several weeks. Second, we focus on a particular parameter of the execution context, the day of the week, and discuss its relevance regarding different weeks.

5. EXPERIMENTAL DATA

To study grid latency, measures were collected by submitting a very large number of probe jobs. These jobs, consisting in the execution of an almost null duration `/bin/hostname` command, are only impacted by the grid latency. In the remainder we make the hypothesis that the users job execution time is known and that therefore only the grid latency varies significantly between different runs of the same computation task. To avoid variations of the system load, a constant number of probes was executing inside the system at any time of the data collection: a new probe was submitted each time another one completed. For each probe job, we logged the job submission date, the job status and the total duration. The probe jobs were assigned a fixed 10000 seconds timeout beyond which they were considered as outliers and canceled. This value is far greater than the average latency observed.

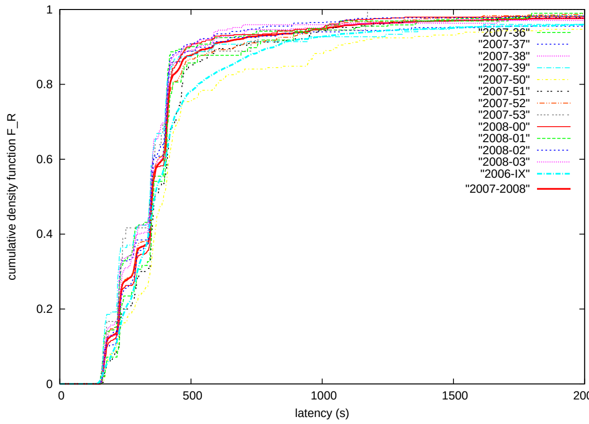

Figure 1: Cumulative density function of the latency for each week, computed on completed jobs.

For the previous work [2], we collected a log gathering 5800 job traces in September 2006 (denoted further as 2006-IX). In this paper, we added 5093 job traces acquired from week 36 to week 39 of 2007 and week 50 of 2007 to week 03 of 2008. The discontinuity of the periods in the new data set is due to our local network failures and does not have any relations with authors choices.

6. ALONG THE WEEKS

Figure 1 presents the cumulative density function of the latency for the different weeks and for the whole period of 2007-2008. The curves concerning the period 2007-2008 presents a similar profile with steps coming from he waiting time of the jobs in the resource brokers (RB). One of the hypothesis is that they could be due to the internal scheduling algorithm of resource broker. Another possible cause might be implementation flaws in the RB code. Those steps have also been observed in the vlemed VO of the EGEE grid. However, an interesting way to compare those curves is to consider the differences between the optimal timeout values that they lead to (computed using equation 1). Figure 2 shows the expectation of execution time for the different weeks. Despite the fact that the different curves present different profiles, the optimal timeout values are visually in the same interval around 400s. These values are more precisely detailed in table 1: the optimal value for 2006 is 528s while values for 2007-2008 are between 422s and 491s. The table presents also, for each period of time, the mean value and the standard deviation of the latency R. In most cases, the reduction of time conducts to a reduction of the standard deviation. Finally the optimal expected execution time is shown. Assuming that the optimal timeout value has been computed in September 2006 (528s), we compute, in table 2, the resulting expectation of execution time and the relative difference with the optimal value computed week by week in order to measure the impact of parameters chosen earlier instead of the optimal one. The relative differences are up to 8%. It happens that this timeout value is greater than all optimal values for the period 2007-2008. The highest differences are obtained when the ascending slope of figure 2 are the highest, which is directly related to the fraction of outliers.

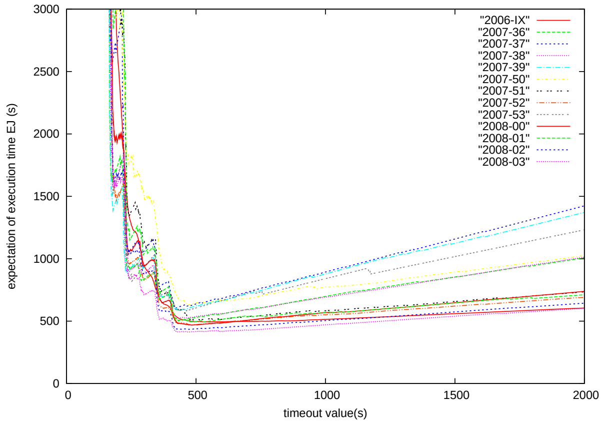

Figure 2: Expectation of job execution time with respect to the timeout value (t_∞). The minimum of each curve gives the best timeout value.

date	R	$\sigma(R)$	outliers	best t_∞	$E_J(t_\infty)$
2006-IX	570s	886s	5%	528s	494s
2007/08	469s	723s	17%	474s	500s
2007-36	446s	748s	24%	423s	502s
2007-37	506s	848s	33%	422s	606s
2007-38	447s	682s	24%	428s	522s
2007-39	489s	741s	32%	436s	585s
2007-50	660s	1046s	18%	467s	628s
2007-51	478s	510s	13%	491s	510s
2007-52	443s	582s	13%	482s	469s
2007-53	375s	238s	31%	432s	581s
2008-00	454s	699s	14%	484s	468s
2008-01	434s	317s	13%	485s	491s
2008-02	418s	547s	12%	433s	435s
2008-03	538s	1196s	10%	474s	413s

Table 1: Mean and standard variation of the latency, fraction of outliers, best timeout value and minimal expectation of execution time. These quantities are computed for the 2006 period, for the 2007-2008 period and for all weeks int the 2007-2008 period.

date	E_J(528s)	ΔE_J	date	E_J(528s)	ΔE_J
2007-36	528s	5.2 %	2007-52	477s	1.7 %
2007-37	648s	7.0 %	2007-53	623s	7.1 %
2007-38	544s	4.2 %	2008-00	475s	1.5 %
2007-39	631s	7.9 %	2008-01	493s	0.4 %
2007-50	652s	3.9 %	2008-02	441s	1.4 %
2007-51	514s	0.9 %	2008-03	418s	1.2 %

Table 2: In this experiment, the timeout value from the period of September 2006 has been used (528s). For each week of the 2007-2008 period, we present the expectation of execution time and the relative difference with the optimal one.

date	E_J(422s)	$\Delta E_J\%$	E_J(491s)	$\Delta E_J\%$
2007-36	505.5	0.7%	527.1	5.0%
2007-37	605.9	0%	632.2	4.3%
2007-38	524.8	0.5%	530.5	1.6%
2007-39	602.9	3.1%	616.8	5.5%
2007-50	718.7	14.5%	642.3	2.3%
2007-51	594.9	16.7%	509.6	0%
2007-52	491.2	4.8%	470.9	0.4%
2007-53	593.7	2.1%	600.0	3.2%
2008-00	501.9	7.2%	470.0	0.4%
2008-01	516.7	5.2%	493.1	0.4%
2008-02	437.0	0.6%	437.2	0.6%
2008-03	419.1	1.5%	414.8	0.5%

Table 3: In this experiment, we focus on data from the period 2007-2008. As determined in table 1, the minimum timeout value is 422s and the maximum is 491s. For these extreme values, the new expectation of execution time and the relative difference with the optimal value are presented.

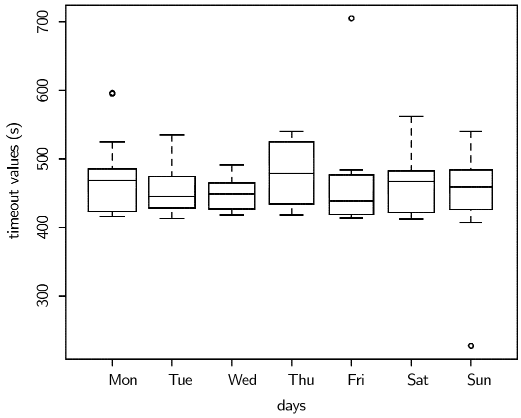

Figure 3: For each day of the week and for each week, the best timeout value is computed. We have plotted boxes for each day of the week. According to ANOVA, there is no significant difference between the days of the week.

Furthermore, we took the minimal and the maximal of timeout values among the different weeks : 422s and 491s. We present the expected execution time for each of these values and the relative differences in table 3. In the case of the maximal timeout value, relative errors are below 6% while in the case of the minimal timeout value, relative errors are up to 17%. This is clearly explained by the shape of the curves on figure 2: the slope of the decreasing part is higher than the slope of the increasing part of each curve. Thus, an overestimation of the timeout value is better than an underestimation, if this overestimation is not too high, which must be quantified. As a conclusion of this part of the study, actualization of the timeout value may improve the total execution time, up to 17%.

7. DAY OF THE WEEK

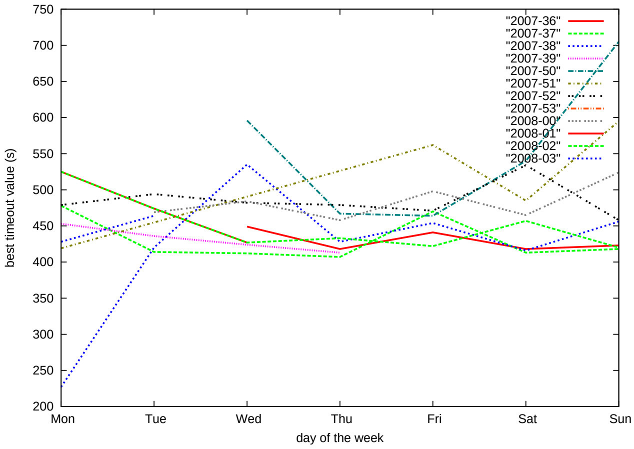

Figure 4: Each curve corresponds to a week of the experiment. The optimal timeout value is plotted with respect to the day of the week.

In this second experiment, we study the influence of the day of the week on the best timeout value: for each week and each day of the week, we compute the best timeout value. These values are plotted on figure 3 with respect to the day of the week. As confirmed by ANOVA analysis, there is no significant difference between the days of the week.

However, in figure 4, we observe that, in most weeks, there is a decrease of best timeout value between Tuesday or Wednesday and Thursday followed by an increase until Friday or Saturday. This profile information thus needs further investigation to be exploited.

8. CONCLUSION

The experiment on the influence of the day of the week shows that it has a hardly relevant impact. The hour of the day could be considered alternatively.

This study shows that variations of the load conditions over long periods of time make it necessarily to update the model parameters along time.

Future work will focus on strategies to perform this update. Moreover, other parameters of the execution context such as the grid resources need to be studied over long period of time.

9. ACKNOWLEDGMENTS

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